Material Selection for PMEDM Process

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***Abstract*—Powder Mixed Electro-Discharge Machining (PMEDM) is a non-traditional machining process. This method is used more and more to machine complex surfaces, parts made from materials with high hardness. Three indispensable components in PMEDM are powder, dielectric fluid and electrode. These components have a great influence on the efficiency of the machining process. This study was conducted to choose the best types for all three components mentioned above. The numbers of powder types, dielectric fluid types and electrode material types considered were ten, three and seven, respectively. The weight of each criterion in each product category was calculated using the two methods Rank Order Centroid (ROC) and Rank Sum (RS). In each case, the two methods were used to rank the alternatives are Faire Un Choix Adéquat (FUCA) (in French) and Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS). The optimal option will be found from the results of ranking the alternatives. The results of ranking the alternatives were also subjected to sensitivity analysis by using Sperman coefficient. This study discovered that the best option found when using the FUCA method is also the best option found when using the MARCOS method, and the best option that was found does not depend on the used weighting method.**

***Keywords*—Powder Mixed Electro-Discharge Machining (PMEDM), powder, dielectric fluid, electrode, Multi-Criteria Decision Making (MCDM), Faire Un Choix Adéquat (FUCA), Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS), weight**

I. INTRODUCTION

Powder Mixed Electro-Discharge Machining (PMEDM) is a machining method that has been widely used to machine parts made of conductive materials [1]. Like the Wire Electrical Discharge Machining process (WEDM), PMEDM is one of the most widely used non-traditional machining processes in current manufacturing [2]. This method can process materials with very high hardness. Since there is no contact between the electrode (tool) and the surface of the work piece, this method can machine thin-walled parts with no fear of deformation of the machined surface. The complex-shaped surfaces can also be processed using the PMEDM method by employing tooling with shaped contours corresponding to the surfaces to be machined. These are the basic advantages of the PMEDM method over other machining methods [3, 4]. The efficiency of the PMEDM machining process depends on many factors such as the parameters of the technology mode, the type of powder, the type of dielectric fluid, the type of electrode, the electrical parameters (amperage, voltage) [5–7]. To improve the efficiency of the PMEDM process, several multi-objective optimization studies using different optimization methods have been carried out. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was used to determine the optimal value of amperage, pulse generation time, pulse stopping time, with the aim of simultaneously ensuring minimum surface roughness and high material removal efficiency when machining alloy INC718 [8]. In this study, the powder that was used was tungsten, the dielectric fluid that was used was kerosene, and the electrode that was used was copper. The TOPSIS method was also used to determine the optimal values of powder concentration, pulse generation time, pulse stopping time, amperage, and polarity of electric current to simultaneously ensure the lowest surface roughness, the highest material removal rate, and the highest machined surface hardness when machining steel [9]. The two methods Multiobjective Optimization On the basis of Ratio Analysis (MOORA) and Weighted Aggregates Sum Product ASsessment (WASPAS) were used to determine the optimal values of powder concentration, amperage, pulse generation time, pulse stopping time, and powder size when machining H11 mold steel [10]. The aim of this study was to simultaneously ensure maximum material removal rate, minimum amount of electrode wear, and minimum surface roughness. The powder material and electrode material that were used in this study were chromium and copper, respectively. The MOORA method was used to determine the optimal values of pulse generation time, pulse stopping time, electrode travel speed, and wire tension (electrode) when machining titanium grade 6 materials [11]. Brass was used as the electrode in this study. This study was carried out to simultanousely ensure the highest dimensional accuracy and minimum roughness. The Multi-Attributive Border Approximation Area Comparison (MABAC) method was used to determine the optimal values of powder concentration, powder size, pulse generation time, pulse stopping time, amperage and voltage to simultanousely ensure minimum surface roughness, maximum material removal rate, and minimum amount of electrode wear when machining 90CrSi

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steel [12]. Four methods including MultiAtributive Ideal-Real Comparative Analysis (MAIRCA), Ranking according to COmpromise Solution (MARCOS), TOPSIS, and Evaluation by an Area-based Method for Ranking (EAMR) were used together to determine the optimal values of powder concentration, powder size, pulse generation time, pulse stopping time, amperage and voltage to ensure the minimum surface roughness and maximum material removal rate when machining SKD11 steel [13]. Although several studies on the optimization of PMEDM machining process have been carried out, some of them have been mentioned above. However, all of those studies focused on determining the optimal value of the technological parameters. The best powder, the best dielectric fluid, and the best electrode material were not found in any published studies. These three components play a decisive role in the effectiveness of the PMEDM process. With each of these components, there are many different options on the market to choose. However, with very different characteristics within each type, choosing the best one is a very complicated task. This research was carried out to select the best powder, the best dielectric fluid, and the best material for making electrodes.

In addition to the multi-objective optimization methods that have been utilized for selecting the values of technological parameters in the PMEDM process, as mentioned above, such as TOPSIS, MOORA, WASPAS, MABAC, MultiAtributive Ideal-Real Comparative Analysis (MAIRCA), MAROS, and EAMR, there are numerous other multi-objective optimization methods. A recent survey has indicated that there are over 200 different multi-objective optimization methods [14]. With such a large number of multi-objective optimization methods available, choosing one or a few methods for implementation poses a challenge for users. Several studies have pointed out that the optimal solution obtained may differ when using different methods [15, 16].

Faire Un Choix Adéquat (FUCA) and MARCOS are two multi-objective optimization methods that have been widely used recently. They are also known by another name as multi-criteria decision- making. FUCA is a multi-objective optimization method that does not require data normalization. This is a distinctive feature of it compared to many other multi-objective optimization methods. This characteristic is an advantage of the FUCA method, meaning that when using the FUCA method to solve a problem, the optimal solution found is independent of data normalization [17, 18]. Recently, this method is being used a lot to determine the optimal option in many fields such as lathe selection [19], grinding machine selection, drilling machine selection, milling machine selection [20], washing machine selection, air conditioner selection, and drone selection [21], etc. However, there have been no studies that have applied this method in optimizing the PMEDM process in general and optimizing the selection of components of the PMEDM system in particular. Using the FUCA method to select powder type, dielectric type and electrode material type is a new point in this article.

MARCOS is a multi-objective optimization method known to have many advantages such as being able to be combined with many different data normalization methods [22], the optimal results found by the MARCOS method are not depends on the weights of the criteria [23]. Another advantage of this method is the minimization of the rank reversal phenomenon. In other words, when using the MARCOS method to solve an optimization problem, the optimal solution found is less influenced by the weights of the criteria as well as the data normalization method used [24]. This method was also used to determine the optimal solution in many fields such as selection of health care service providers [25], selection of suppliers in the footwear manufacturing industry [26], selection of milling method [27], selection of forklift type [28], etc. However, this method has never been used to select system components in PMEDM. The simultaneous use of FUCA and MARCOS methods in the process of selecting powder materials, selecting dielectrics, and selecting electrode materials not only exploits the advantages of these two methods but is also a novelty compared to previously available documents.

II. Two Used Multi-objective Optimization Methods

A. The FUCA Method

To determine the optimal option among *m* options, the use of the FUCA method is performed in the following sequence [17, 18]:

Build a decision matrix with *m* rows and *n* columns, where *m* and *n* are the number of options and the number of criteria for each option, respectively. Let r_{ij} be the rank of criterion *j* of option *i*, with $j = 1 - n$, $i = 1 - m$.

Rank the alternatives for each criterion, $r_{ij} = 1$ if option *i* with criterion *j* is the best. In contrast, if option *i* has the worst criterion *j*, then $r_{ij} = m$.

The score v_i of option *i* is calculated according to Eq. (1).

$$v_i = \sum_{j=1}^{n} r_{ij}.w_j \tag{1}$$

where, w_j is the weight of the criterion *j*.

The alternative with the smallest score is the optimal solution, and vice versa.

B. The MARCOS Method

Use the MARCOS method to determine the optimal option in the following order [29]:

Build a decision matrix (similar to the FUCA method).

Add to the decision matrix two options, including the ideal alternative (AI) and the alternative oppose the ideal alternative (AAI).

where:

+ For the larger the better criteria.

$$AAI = min\ (y_{ij}); \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n. \tag{2}$$

$$AI = max\ (y_{ij}); \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n. \tag{3}$$

+ For the smaller the better criteria.

$$AAI = max\ (y_{ij}); \tag{4}$$

$i = 1, 2, \ldots, m; j = 1, 2, \ldots, n.$

$$AI = min\ (y_{ij}); \tag{5}$$

$i = 1, 2, \ldots, m; j = 1, 2, \ldots, n.$

Eqs. (6) and (7) are used to calculate normalized values.
+ For the smaller the better criteria.

$$u_{ij} = \frac{y_{AI}}{y_{ij}} \tag{6}$$

+ For the larger the better criteria.

$$u_{ij} = \frac{y_{ij}}{y_{AI}} \tag{7}$$

Eq. (8) is used to calculate the weighted normalized values of the criteria.

$$c_{ij} = u_{ij} \times w_j \tag{8}$$

The coefficients K_i^+ and K_i^- are calculated according to Eqs. (8) and (9).

$$K_i^- = \frac{S_i}{S_{AAI}} \tag{9}$$

$$K_i^+ = \frac{S_i}{S_{AI}} \tag{10}$$

where: S_i, S_{AAI} and S_{AI} are the total values of c_{ij}, y_{aai} and y_{ai}, respectively, with $i = 1, 2, \ldots, m$.

The two quantities $f(K_i^+)$ and $f(K_i^-)$ are calculated according to Eqs. (11) and (12).

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{11}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{12}$$

The score $f(Ki)$ of alternative i is calculated according to Eq. (13).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{13}$$

The alternative with the highest score is the optimal option, and vice versa.

III. Two Used Weighting Methods

To choose the best material in PMEDM, it is necessary to determine the priority of the criteria for each material. If this is not done, it will lead to serious mistakes in material selection. For example, when choosing powder, if we do not prioritize the criteria and choose a powder with high density, most of the particles will fall to the bottom of the tank. The number of particles in the machining process will be very little. Then no matter how good the other parameters of the powder are, their effect on the machining process will not be significant [30, 31]. A small example above shows that prioritizing criteria is very important for the PMEDM process. *ROC* and *RS* are two of several weighting methods for criteria based on their prioritization [32, 33]. These are also the two simplest methods of determining weights. The use of each of these methods requires only a single formula [32, 33]. For this reason, these two methods were used in this study.

After arranging the criteria in descending order of priority, the weights of the criteria are determined according to the two methods *ROC* and *RS* according tot Eqs. (14)–(5), respectively [32, 33].

$$w_j = \frac{1}{n}\sum_{k=i}^{n}\frac{1}{k} \tag{14}$$

$$w_j = \frac{2(n+1-i)}{n(n+1)} \tag{15}$$

IV. Material Selection IN Pmedm

A. Powder Material Selection

Ten commonly used powders in *PMEDM* include Aluminum, Chromium, Silicon Carbide, Silicon, Tungsten, Titanium, Molybdenum Disulfide, Graphite, Molybdenum, Alumina. According to chemical notation, they have been named Al, Cr, SiC, Si, W, Ti, MoS_2, Gr/C, Mo, and Al_2O_3, respectively. The five parameters of each material are Density, Thermal conductivity, Electrical conductivity, Melting point, and Specific heat. The values and units of each parameter of each powder type are presented in Table I [34].

TABLE I. Some Powder Types

Material	Density	Thermal Conductivity	Electrical Conductivity	Melting Point	Specific Heat
	g/cm^3	W/(cm .°C)	μΩ/cm	°C	cal/ (g.°C)
Al	2.7	2.38	2.45	660	0.215
Cr	7.16	0.67	12.7	1875	0.11
SiC	3.21	3	10^9	2975	0.18
Si	2.33	1.5	10^5	1410	0.17
W	19.3	1.673	5.6	3410	0.031
Ti	4.72	0.22	55	1668	0.125
MoS_2	5.06	0.138	106	1185	0.07
Gr/C	1.63	2.47	1750	4550	0.185
Mo	10.2	1.39	5.27	2610	0.06
Al_2O_3	3.98	0.251	103	2072	0.17

The density of the powder has a great influence on the efficiency of the machining process. If the powder has high density, it tends to fall to the bottom of the tank, then the role of the powder in the machining process will be reduced [30]. In contrast, if the powder has a small density, it will be suspended in the dielectric fluid, its positive effects on the machining process will be noted [31]. This means that it is always desirable to use powders with low density. In other words, the density of the powder is the smaller the better criteria.

The parameters of thermal conductivity, electrical conductivity, melting point and specific heat of the powder also have a great influence on the machining process. The higher the values of the four parameters of the powder, the higher its durability. This will reduce the rate of deterioration of the powder during use. If these parameters have great values, it also helps to keep the accuracy of the shape and size of the powder for a long time, reducing the cost of adding powder to the storage tank or the cost of replacing the whole powder [35–37]. In other words, all four parameters are the larger the better criteria.

However, according to the data in Table I, it shows that the smallest powder density belongs to the Gr/C powder, the largest electrical and thermal conductivity coefficients belong to the SiC powder, the highest melting temperature belongs to the Gr/C powder, and the largest specific heat belongs to Al powder. That is, there is no type of powder whose all five parameters are the best. Choosing a type of powder based only on a certain parameter will not guarantee that the best type of powder is chosen. The best powder type can be found only when all of its parameters are considered. This can be done using multi-objective optimization methods. Two methods FUCA and MARCOS will be used to solve this problem. However, when applying these two methods, it is necessary to determine the weights for the criteria. Among the five parameters of powder types, the priority level decreases in the order of Density, Thermal conductivity, Melting point, Electrical conductivity, Specific heat [38, 39]. In Table II, the weights of the criteria when calculated by two different methods are summarized.

B. Applying the FUCA Method

For each criterion, the ranks of the options weredetermined, the results were shown in Table III.

TABLE II. WEIGHTS OF THE CRITERIA

Weight Method	**Density**	**Thermal Conductivity**	**Electrical Conductivity**	**Melting Point**	**Specific Heat**
	Order of priority				
	(1)	(2)	(4)	(3)	(5)
	Weight				
ROC	0.4567	0.2567	0.0900	0.1567	0.0400
RS	0.3333	0.2667	0.1333	0.2000	0.0667

TABLE III. RANKS OF THE OPTIONS FOR EACH CRITERION

Material	**Density**	**Thermal Conductivity**	**Electrical Conductivity**	**Melting Point**	**Specific Heat**
Al	3	3	10	10	1
Cr	8	7	7	6	7
SiC	4	1	1	3	3
Si	2	5	2	8	4.5
W	10	4	8	2	10
Ti	6	9	6	7	6
MoS_2	7	10	4	9	8
Gr/C	1	2	3	1	2
Mo	9	6	9	4	9
Al_2O_3	5	8	5	5	4.5

Eq. (1) was applied to calculate the scores of the powders. This was done twice corresponding to two different weighting methods, the results have been summarized in Table IV. The ranks of the powder types were also summarized in this table.

The ranking of powder types when using the FUCA method has been completed. We see that 8/10 powder types have the same ranking when using two different methods to calculate weights for the criteria. In both examined cases, the powder types that ranked the 1st, 2nd, 3rd, 4th, 5th, 8th, 9th, and 10th are completely identical. Accordingly, Gr/C is the best type, whereas MoS_2 is the worst type, meaning the optimal option is Gr/C. The next thing to be done in this section is to determine the optimal option when using the MARCOS method.

TABLE IV. SCORES AND RANKS OF THE OPTIONS

Material	**Weight Method**			
	ROC		**RS**	
	$\mathbf{v_i}$	**Rank**	$\mathbf{v_i}$	**Rank**
Al	4.6467	4	5.2000	4
Cr	7.3000	8	7.1333	8
SiC	2.7633	2	2.5333	2
Si	3.8100	3	4.1667	3
W	7.0267	7	6.5333	6
Ti	6.9267	6	7.0000	7
MoS_2	7.8533	10	7.8667	10
Gr/C	1.4767	1	1.6000	1
Mo	7.4467	9	7.2000	9
Al_2O_3	5.7500	5	5.7667	5

A. Apply the MARCOS Method

Applying the Eqs. (2)–(7), the calculated standardized values were shown in Table V.

The weighted normalized values of the criteria were calculated according to Eq. (8). First, the weights of the criteria determined by the ROC method were used. The calculation results were presented in Table VI.

Some other parameters have been calculated according to Eqs. (9)–(13), the results have been summarized in Table VII. The ranks of the powder types were also determined and placed in the last column of this table.

In the same way, the values of some parameters in the MARCOS method were calculated when the weights of the criteria were determined by the RS method. All calculated values and ranks of powder types were summarized in Table VIII.

TABLE V. NORMALIZED VALUE

Material	Density	Thermal Conductivity	Electrical Conductivity	Melting Point	Specific Heat
Al	0.6037	0.7933	0.0000	0.1451	1.0000
Cr	0.2277	0.2233	0.0000	0.4121	0.5116
SiC	0.5078	1.0000	1.0000	0.6538	0.8372
Si	0.6996	0.5000	0.0001	0.3099	0.7907
W	0.0845	0.5577	0.0000	0.7495	0.1442
Ti	0.3453	0.0733	0.0000	0.3666	0.5814
MoS_2	0.3221	0.0460	0.0000	0.2604	0.3256
Gr/C	1.0000	0.8233	0.0000	1.0000	0.8605
Mo	0.1598	0.4633	0.0000	0.5736	0.2791
Al_2O_3	0.4095	0.0837	0.0000	0.4554	0.7907

TABLE VI. THE WEIGHTED NORMALIZED VALUES OF THE CRITERIA

Material	Density	Thermal Conductivity	Electrical Conductivity	Melting Point	Specific Heat
Al	0.2757	0.2036	0.0000	0.0227	0.0400
Cr	0.1040	0.0573	0.0000	0.0646	0.0205
SiC	0.2319	0.2567	0.0900	0.1024	0.0335
Si	0.3195	0.1283	0.0000	0.0485	0.0316
W	0.0386	0.1431	0.0000	0.1174	0.0058
Ti	0.1577	0.0188	0.0000	0.0574	0.0233
MoS_2	0.1471	0.0118	0.0000	0.0408	0.0130
Gr/C	0.4567	0.2113	0.0000	0.1567	0.0344
Mo	0.0730	0.1189	0.0000	0.0899	0.0112
Al_2O_3	0.1870	0.0215	0.0000	0.0713	0.0316

TABLE VII. SOME PARAMETERS IN MARCOS AND RANKING OF OPTIONS WHEN THE WEIGHTS OF THE CRITERIA WERE CALCULATED USING THE ROC METHOD

Material	Ki–	Ki+	f(Ki–)	f(Ki+)	f(Ki)	Rank
l	0.0008	5.42×10^{-10}			5.42×10^{-10}	3
Cr	0.0004	2.46×10^{-10}			2.46×10^{-10}	9
SiC	0.0010	7.14×10^{-10}			7.14×10^{-10}	2
Si	0.0008	5.27×10^{-10}			5.27×10^{-10}	4
W	0.0004	3.04×10^{-10}	6.81×10^{-7}	0.9999	3.04×10^{-10}	6
Ti	0.0004	2.57×10^{-10}			2.57×10^{-10}	8
MoS2	0.0003	2.12×10^{-10}			2.12×10^{-10}	10
Gr/C	0.0013	8.59×10^{-10}			8.59×10^{-10}	1
Mo	0.0004	2.92×10^{-10}			2.92×10^{-10}	7
Al2O3	0.0005	3.11×10^{-10}			3.11×10^{-10}	5

TABLE VIII. SOME PARAMETERS IN MARCOS AND RANKING OF ALTERNATIVES WHEN THE WEIGHTS OF CRITERIA WERE CALCULATED BY THE RS METHOD

Material	Ki–	Ki+	f(Ki–)	f(Ki+)	f(Ki)	Rank
Al	0.0007	5.08×10^{-10}			5.08×10^{-10}	3
Cr	0.0004	2.51×10^{-10}			2.51×10^{-10}	8
SiC	0.0011	7.55×10^{-10}			7.55×10^{-10}	2
Si	0.0007	4.81×10^{-10}			4.81×10^{-10}	4
W	0.0005	3.36×10^{-10}	6.81×10^{-7}	0.9999	3.36×10^{-10}	5
Ti	0.0004	2.46×10^{-10}			2.46×10^{-10}	9
MoS_2	0.0003	1.93×10^{-10}			1.93×10^{-10}	10
Gr/C	0.0012	8.10×10^{-10}			8.10×10^{-10}	1
Mo	0.0005	3.10×10^{-10}			3.10×10^{-10}	6
Al_2O_3	0.0004	3.02×10^{-10}			3.02×10^{-10}	7

The ranking of powder types using the MARCOS method was also concluded with both cases of the weights of the criteria calculated by two different methods. We see that the powder types that ranked the 1st, 2nd, 3rd and 10th are completely identical when the weights were calculated by two different methods. Accordingly, Gr/C was determined to be the best, and MoS_2 was determined to be the worst (see Table VIII).

Fig. 1 is a chart comparing the ranking results of powder types in four different cases. For the convenience of graph presentation, the combination of the FUCA method and the ROC weight method is abbreviated as FUCA & ROC, similarly, the combination of the FUCA method and the RS weight method is abbreviated as FUCA & RS, etc.

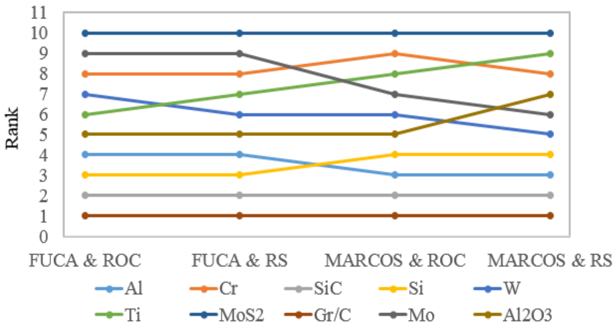

Fig. 1. Ranks of powder types.

It is found that in all surveyed cases, Gr/C is always determined to be the optimal solution, SiC always ranks the 2nd, and MoS_2 always ranks the 10th. To make sure Gr/C is the optimal option, sensitivity analysis when using MCDM methods is necessary [40, 41]. Sperman rank correlation coefficient was used for sensitivity analysis [42–44], which is calculated by Eq. (16).

$$S = 1 - \frac{6\sum_{i=1}^{m} D_i^2}{m(m^2-1)} \tag{16}$$

where *Di* represents the rank difference of the alternatives of a certain scenario compared to another scenario, *m* is the number of alternatives to be ranked. Call each combination of a multi-objective optimization method and a weighting method for the criteria a scenario, so in this case we have ranked the powders according to four different scenarios, S1, S2, S3, S4. In which S1, S2, S3, S4 correspond to the scenarios FUCA & ROC, FUCA & RS, MARCOS & ROC, and MARCOS & RS. The Sperman coefficients were calculated as shown in Table IX.

TABLE IX. SPERMAN COEFFICIENT VALUES

Scenario	Si	S1	S2	S3	S4
Si	1	0.9879	0.9273	0.8303	0.9515
S1	0.9879	1	0.9879	0.9273	0.8303
S2	0.9273	0.9879	1	0.9515	0.8788
S3	0.8303	0.9273	0.9515	1	0.9515
S4	0.9515	0.8303	0.8788	0.9515	1

The data in Table IX show that the Sperman coefficients on the hierarchical correlation of the alternatives is in the range S ∈ [0.9303, 1], which shows a very high degree of correlation. This shows that the change in the rank of powder types is not significant even after being performed in four different scenarios. That gives us solid confidence in the ranking results of the options. Accordingly, it is firmly established that Gr/C is the best powder among the ten considered types. This powder has values for the corresponding parameters of density, thermal conductivity, electrical conductivity, melting point, and specific heat, which are 1.63 (g/cm^3), 2.47 (W/(cm.°C)), 1750 (μΩ/cm), 4550 (°C), and 0.185 (cal/(g.°C)), respectively. This powder type has also been extensively used in several recent research studies [34].

B. Dielectric Selection

Three types of dielectrics commonly used in *PMEDM* include Kerosene, Mineral oil, and Silicon oil. When choosing dielectric fluids, several parameters need to be considered simultaneously. Among them, four key parameters deserve more attention, including specific heat, thermal conductivity, dielectric strength, and flash point. The dielectric fluid should have a sufficiently high specific heat to absorb and retain the heat generated by the electric current passing through. This helps reduce the risk of overheating and ensures stability during processing. The thermal conductivity of the dielectric fluid needs to be sufficient for effective heat dissipation, aiding in temperature control in the machining area. A good level of thermal conductivity can facilitate rapid cooling of areas affected by electrodes. Dielectric strength is the ability of the dielectric fluid to resist breakdown under the influence of an electric field. This is crucial to prevent arcing and minimize electrical incidents. The flash point is the minimum temperature at which a substance needs to emit enough vapor to form a flammable mixture when exposed to a flame or high heat source. In PMEDM, the dielectric fluid should have a sufficiently high flash point to ensure safety during use. The values and units of these parameters were summarized in Table X [34]. These four parameters are all parameters that users want to be as large as possible. In other words, they are all criteria of the larger the better type.

Determining the best dielectric fluid type among the three investigated types will not be able to achieve accurate results if base only on observing the data in Table X. The explanation for this statement is as follows Specific heat and Breakdown strength have the greatest values belonging to Kerosene, while Thermal conductivity and Flashpoint have the greatest value belonging to Silicon oil. Thus, it is necessary to use the two methods FUCA and MARCOS to find the best dielectric fluid type. Accordingly, determining the weights for the criteria needs to be done. Through specialized literature, it has been found that the importance of parameters decreases in order of Specific heat, Breakdown strength, Thermal conductivity, and Flashpoint [45]. Table XI lists the weighted values of these parameters when calculated by two different methods.

The ranking of dielectric fluid types using the FUCA and MARCOS methods was also done similarly to Section

IV.A. Fig. 2 is a chart representing the ranks of dielectric fluid types.

The results of ranking dielectric fluid types (Fig. 2) show that in all implemented scenarios, Kerosene is always determined to be the best type. Sensitivity analysis was again performed in this case. Sperman rank correlation coefficient values were calculated and summarized in Table XII.

TABLE X. TYPES OF DIELECTRIC [34]

Dielectric Name	Specific Heat	Thermal Conductivity	Breakdown Strength	Flashpoint
	J/kg-K	W/mK	kV/mm	°C
Kerosene	2100	0.14	24	51
Mineral Oil	1860	0.13	12.5	160
Silicon Oil	1510	0.15	12.5	300

TABLE XI. WEIGHTS OF THE CRITERIA

Weight Method	Specific Heat	Thermal Conductivity	Breakdown Strength	Flashpoint
	(1)	(3)	(2)	(4)
ROC	0.5208	0.1458	0.2708	0.0625
RS	0.4	0.2	0.3	0.1

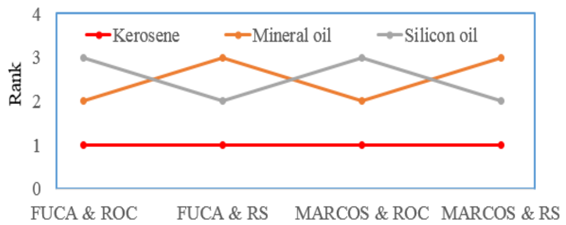

Fig. 2. Ranking of dielectric types.

The data in Table XII shows the Speman coefficients on the rank correlation of the options is in the range S ∈ [0.5, 1], showing a fairly high level of correlation, meaning the ranks of the options do not change much in different scenarios. This helps us believe in the accuracy of the results of ranking the options. Thus, among the three considered types of dielectrics, Kerosene is definitely confirmed to be the best. This dielectric substance has a specific heat of 2000 (J/kg-K), thermal conductivity of 0.14 (W/mK), breakdown strength of 24 (kV/mm), and flashpoint of 51 (°C). It is also a type of dielectric material that has been utilized in numerous recent research studies [34, 46].

TABLE XII. VALUES OF SPERMAN COEFFICIENTS

Scenario	Si	S1	S2	S3	S4
Si	1	0.5	1	0.5	0.5
S1	0.5	1	0.5	1	0.5
S2	1	0.5	1	0.5	1
S3	0.5	1	0.5	1	0.5
S4	0.5	0.5	1	0.5	1

C. Electrode Material Selection

In Table XIII, the information about seven types of materials commonly used to make electrodes in PMEDM is presented. Each of these materials was also described by seven different parameters [34]. The four parameters that are the smaller the better include Density, Tool Wear Rate, Cost, and Manufacturing. The three remaining parameters (Melting temperature, Thermal conductivity, Material Removal Rate) are in the form of the larger the better [47, 48].

TABLE XIII. TYPES OF ELECTRODE MATERIALS

Material	Density	Melting Temperature	Thermal Conductivity	Material Removal Rate	Tool Wear Rate	Cost	Manufacturing
	g/cm^3	°C	W/m.k		-	-	-
Copper	8.96	1084	401	High	Low	High	Easy
Brass	8.73	930	159	High	High	Low	Easy
Tungsten	19.25	3695	173	Low	Lowest	High	Difficult
Tungsten Copper Alloy	15.2	3500	27.21	Low	Low	High	Difficult
Carbon Steel	7.85	1460	51.9	Low	High	Low	Easy
Zink Based Alloy	7.14	693	116	High	High	High	Easy
Graphite	1.811	3350	1400	High	Low	High	Difficult

Once again, we see that if we only observe the data in Table XI, we will not be able to find the best material to make electrodes. The cells containing the best value of each criterion are highlighted in Table XIII, and there is no row whose cells are all highlighted. For this reason, the two methods FUCA and MARCOS are used to find the best material.

To determine the weights for the criteria according to the two methods ROC and RS, their prioritization was performed [49, 50]. The priorities of the criteria and their weights were determined and summarized in Table XIV.

Since there are four parameters in Table XIII in qualitative form, the conversion of these linguistic variables into numerical variables was performed. This method was done according to some published studies [51]. For Material Removal Rate criteria, assign *"High = 1"*, *"Low =0.5"*; for Tool Wear Rate criteria, assign *"High = 0.75"*, *"Low = 0.5"*, *"Lowest = 0.25"*; for Cost criteria, assign *"High = 0.5"*, *"Low = 0.25"*; and finally for the Manufacturing criteria, assign *"Easy = 0.25"*, *"Difficulty = 0.5"*.

Ranking of electrode materials using the two methods *FUCA*, *MARCOS* and two weighting methods (*ROC* and *RS*) was also performed, the results were graphed in Fig. 3.

TABLE XIV. WEIGHTS OF THE CRITERIA

Weight Method	Density	Melting Temperature	Thermal Conductivity	Material Removal Rate	Tool Wear Rate	Cost	Manufacturing
	(1)	(7)	(6)	(5)	(2)	(4)	(3)
	Weight						
ROC	0.3704	0.0204	0.0442	0.0728	0.2276	0.1085	0.1561
RS	0.2500	0.0357	0.0714	0.1071	0.2143	0.1429	0.1786

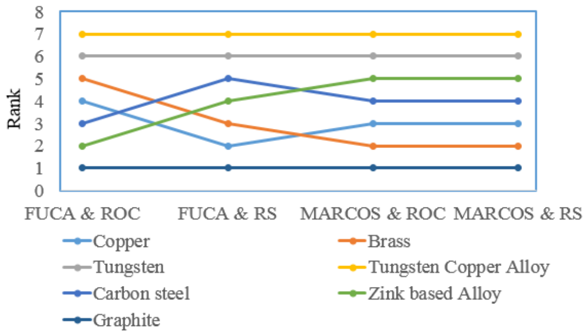

Fig. 3. Ranking of electrode materials.

It is found that the results of ranking seven electrode materials by the *MARCOS* method are not affected by the weights of the criteria. This has also been observed in some previous studies [32]. In all four investigated scenarios, Graphite is always ranked the 1st, Tungsten is always ranked the 6th, and Tungsten Copper Alloy is always ranked the 7th. Once again sensitivity analysis was performed. In this case, the Sperman rank correlation coefficient values were calculated and summarized in Table XV.

TABLE XV. VALUES OF THE SPERMAN COEFFICIENTS

Scenario	Si	S1	S2	S3	S4
Si	1	0.7143	0.6429	0.6429	0.9286
S1	0.7143	1	0.7143	0.6429	0.6429
S2	0.6429	0.7143	1	0.9286	0.9286
S3	0.6429	0.6429	0.9286	1	1
S4	0.9286	0.6429	0.9286	1	1

The data in Table XV shows that Sperman coefficients on the hierarchical correlation of the alternatives is in the range S $\in$ [0.6429, 1] showing a very high degree of correlation. That proves that the ranks of the options are just a little different when ranked in different scenarios. Thus, we firmly affirm that Graphite is the best material for making electrodes. Graphite electrodes have a density of 1.811 (g/cm^3), a melting temperature of 3350 (°C), thermal conductivity of 1400 (W/m.k), a high material removal rate, slow electrode wear rate, relatively high cost, and are a type of material that is relatively difficult to process. Some recent studies on PMEDM have also employed this material for electrode fabrication [34, 52, 53].

V. CONCLUSION

Powder, dielectric fluid and electrode are three very important components in PMEDM. In this study, the selection of the best type for all three components was carried out. The two methods FUCA and MARCOS were used to perform this task. In each case, the weights of the criteria were also calculated according to two different methods, ROC and RS. In each case, a sensitivity analysis of the results of ranking the options was also performed. Some conclusions are drawn as follows:

- The best solution determined by the FUCA method is always the same as when using the MARCOS method, and does not depend on the used weighting method.
- Among ten types of powder including Al, Cr, SiC, Si, W, Ti, MoS_2, Cr/C, Mo and $Al2O_3$, Cr/C is the best.
- Kerosene is the best among three types of dielectric fluids including Kerosene, Mineral oil, and Silicon oil.
- Graphite is the best material for making electrodes out of seven types including Copper, Brass, Tungsten, Tungsten Copper Alloy, Carbon steel, Zink based Alloy, and Graphite.
- Experimental studies to compare the effectiveness of PMEDM method when using different types of materials (powder, dielectric solution, electrode) is what needs to be done in the future to verify the results obtained in this study.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Nguyen Van Thien is the first author who wrote methodology, wring original draft, configured. Nguyen Hong Son is correspondent who reviewed and edited project administration, methodology. All authors had approved the final version.

REFERENCES

[1] S. Biswal *et al.*, "MCDM optimization of electrical discharge machined Al-WC–B4C hybrid composite using Taguchi-

MARCOS method," *Materialstoday: Proceedings*, vol. 74, no. 4, pp. 587−594, 2023.

[2] A. Kumar, V. Kumar, and J. Kumar, "Multi-response optimization of process parameters based on response surface methodology for pure titanium using WEDM process," *The International Journal of Advanced Manufacturing Technology*, vol. 68, pp. 2645–2668, 2013.

[3] M. Ashok, T. Niranjan, S. Chokalingam, and B. Singaravel, "Investigation of powder mixed electrical discharge machining and process parameters optimization using Taguchi based overall evaluation criteria," in *Proc. IOP Conf. Series: Materials Science and Engineering*, vol. 1057, 012075, 2021.

[4] P. D. Partha and C. Shankar, "Parametric optimization of non-traditional machining processes using TAGUCHI method and super ranking concept," *Yugoslav Journal of Operations Research*, vol. 29, no. 2, pp. 249–271, 2019.

[5] B. Jabbaripour, M. H. Sadegh, M. R. Shabgard, S. Shajari, and H. Hassanpou, "Investigating the effects of powder mixed electrical discharge machining on the surface quality of γ–TiAl intermetallic," *Advanced Materials Research*, vol. 488−489, pp. 396−401, 2012.

[6] S. Srivastava, M. Vishn, M. T. Gangadhar, and V. Kuksha, "An insight on powder mixed electric discharge machining: A state of the art review," in *Proc. Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 237, no. 5, 2022.

[7] H. Rajkumar and M. Vishwakamra, "Performance parameters characteristics of PMEDM: A review," *International Journal of Applied* Engineering *Research*, vol. 13, no. 7, pp. 5281−5290, 2018.

[8] J. Jayaraj, R. Sundaresan, and S. Chinnamuthu, "Multi-criteria decision of W-powder mixed electro discharge drilling parameters using TOPSIS approach," *MECHANIKA,* vol. 25, no. 1, pp. 52–56, 2019.

[9] N. D. Luan, N. D. Minh, and L. T. P. Thanh, "Multi-objective optimization of PMEDM process parameter by topsis method," *International Journal of Trend in Scientific Research and Development,* vol. 3, no. 4, pp. 112–115, 2019.

[10] A. Jaiswal, B. Peshwani, S. Chakrabort, and B. B. Pradhan, "Multi response optimization of powder mixed electro discharge machining using MOORA and WASPAS," *International Journal on Advanced Electrical and Computer Engineering*, vol. 5, no. 2–3, pp. 110–114, 2018.

[11] H. Majumder and K. Mait, "Optimization of machining condition in WEDM for titanium grade 6 using MOORA coupled with PCA a multivariate hybrid approach," *Journal of Advanced Manufacturing Systems*, vol. 16, no. 2, pp. 81–99, 2017.

[12] N. H. Linh, P. D. Phong, T. Muthuramalingam, T. M. Tan, T. H. Danh, V. N. Pi, H. X. Tu, and N. V. Tung, "Determination of best input factors for PMEDM 90CrSi tool steel using MABAC method," *Advances in Engineering Research and Application*, vol. 602, pp. 335–344, 2022.

[13] T. H. Danh, T. Q. Huy, P. D. Lam, N. M. Cuong, H. X. Tu, and V. N. Pi, "A study on multi-criteria decision-making in powder mixed electric discharge machi ning cylindrical shaped parts," *EUREKA: Physics and Engineering*, vol. 2022, no. 5, pp. 123–139, 2022.

[14] M. Baydaş, T. Eren, Ž. Stević, V. Starčević, and R. Parlakkaya, "Proposal for an objective binary benchmarking framework that *validates* each other for comparing MCDM methods through data analytics," *PeerJ Computer Science*, 2023.

[15] T. V. Huy, N. Q. Quyet, V. H. Binh, T. M. Hoang, N. T. T. Tien, L. T. Anh, D. T. Nga, N. Q. Doan, P. H. Tu, and D. D. Trung, "Multi-criteria *decision*-making for electric bicycle selection," *Advanced Engineering Letters,* vol. 1, no. 4, pp. 126–135, 2022.

[16] D. D. Trung, "Expanding data normalization method to CODAS method for multi-criteria decision making," *Applied Engineering Letters,* vol. 7, no. 2, pp. 54–66, 2022.

[17] M. M. L Fernando *et al.*, "Selecting the best alternative based on a hybrid multiobjective GA-MCDM approach for new product development in the pharmaceutical industry," in *Proc. IEEE Symposium on Computational Intelligence in Multicriteria Decision-Making (MDCM)*, 2021.

[18] H. X. Thinh, "Multi-objective optimization of turning process by FUCA method," *Strojnícky Casopis Journal of Mechanical Engineering*, vol. 73, no. 1, pp. 55−66, 2023.

[19] D. D. Trung, N. X. Truong, and H. X. Thinh, "*Combined PIPRECIA* method and modified FUCA method f*or* selection of lathe," *Journal of Applied Engineering Science*, vol. 20, no. 4, pp. 1355–1365, 2022.

[20] N. H. Son, T. T. Hieu, N. M. Thang, H. N. Tan, N. T. Can, P. T. Thao, and N. C. Bao, "Choosing the best machine tool in mechanical manufacturing," *EUREKA: Physics and Engineering*, no. 2, pp. 97−109, 2023.

[21] N. Anh-Tu, "Combining fuca, curli, and weighting methods in the decision-making of selecting technical products," *Engineering, Technology and Applied Science Research*, vol. 13, no. 4, pp. 11222–11229, 2023.

[22] D. D. Trung, "Development of data normalization methods for multi-criteria decision making: Applying for MARCOS method," *Manufacturing Review*, vol. 9. no. 22, 2022.

[23] D. D. Trung, "Multi-criteria decision making under the MARCOS method *and* the weighting methods: Applied to milling, grinding and turning processes," *Manufacturing Review*, vol. 9, no. 3, 2022.

[24] A. E. Araby, "The utilization of MARCOS method for different engineering applications: A comparative study," *International Journal of Research in Industrial Engineering*, 2023.

[25] Z. Stevic, D. Pamucar, A, Puska, and P. Chatterjee, "Sustainable *supplier* selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS)," *Compueters & Industrial Engineering,* vol. 140, 106231, 2020.

[26] W. C. Nan, T. T. T. Nguyen, D. T. Tuan, and N. N. A. Thy, "A hybrid OPA and fuzzy MARCOS methodology for sustainable supplier selection with technology 4.0 evaluation," *Processes*, vol. 10, 2351, 2022.

[27] D. D. Trung, "Application of EDAS, MARCOS, TOPSIS, MOORA and PIV *methods* for multi-criteria decision making in milling process," *Strojnícky Časopis Journal of Mechanical Engineering*, vol. 71, no. 2, pp. 69–84, 2022.

[28] E. Huskanovic, Z. Stevic, and S. Simic, "Objective-subjective CRITIC-MARCOS model for selection forklift in internal transport technology processes," *Mechatronics and Intelligent Transportation Systems,* vol. 2, no. 1, pp. 20–21, 2023.

[29] Z. Stevic, D. Pamucar, A. Puska, and P. Chatterjee, "Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement alternatives and ranking according to COmpromise solution (MARCOS)," *Computers & Industrial Engineering*, vol. 140, pp. 1–33, 2020.

[30] W. S. Zhao, Q. G. Meng, and Z. L. Wang, "The application of research on powder mixed EDM in rough machining," *Journal of Materials Processing Technology*, vol. 129, no. 1–3, pp. 30–33, 2002.

[31] Z. Z. Lu, F. L. Zhao, and Y. Y. Yang, "Research on dielectric *breakdown* and discharge channel in powder-mixed EDM," *Dalian Ligong Daxue Xuebao/Journal of Dalian University of Technology*, vol. 48, no. 3, pp. 373–377, 2008.

[32] K. Aliyev, A. Aliyev, R. Aliyev, and M. Ozdese, "Application of fuzzy simple additive weighting method in group decision-making for capital investment," *Axioms*, vol. 12, 797, 2023.

[33] N. H. Son and T. T. Hieu, "Selection of welding robot by multi-criteria decisionmaking method," *Eastern-European Journal of Enterprise Technologies*, vol. 1–3, 121, 2023.

[34] A. Y. Joshi and A. Y. Joshi, "A systematic review on powder mixed electrical discharge machining", *Heliyon*, vol. 5, e02963, pp. 1–12, 2019.

[35] X. Zhu, G. Li, J. Mo, and S. Ding, "Electrical discharge machining of semiconductor materials: A review", *Journal of Materials Research and Technology*, vol. 25, pp. 4354–437, 2023.

[36] Y. Jiang, L. Kong, J. Yu, C. Hua, and W. Zhao, "Experimental research on preparation and machining performance of porous electrode in electrical discharge machining", *Journal of Mechanical Science and Technolog*, vol. 36, pp. 6201–6215, 2022.

[37] D. P. Van, S. Shirguppikar, P. N. Huu, M. Thangaraj, T. L. T. Phuong, L. N. Trong, and V. Ganachari, "Influence of graphene coating in electrical discharge machining with an aluminum electrode," *Journal of the Mechanical Behavior of Materials*, vol. 32, 2022028, pp. 1–10, 2023.

[38] Y. H. Guu and H. Hocheng, "Effects of workpiece rotation on *machinability* during electrical discharge machining," *J. Mater. Manuf. Process*, vol. 16, no. 1, pp. 91–101, 2001.

[39] Y. S. Wong, L. C. Lim, I. Rahuman, and W. M. Tee, "Near-mirror-finish phenomenon in EDM using powder-mixed dielectric," *J. Mater. Process, Technol*, vol. 79, no. 1–3, pp. 30–40, 1998.

[40] D. Bozanic, A. Milic, D. Tesic, W. Sałabun, and D. Pamucar, "D numbers-fucom-fuzzy rafsi model for selecting the group of construction machines for enabling mobility," *Facta Universitatis - Mechanical* Engineering, vol. 19, no. 3, pp. 447–471, 2021.

[41] L. J. Muhammad, I. Badi, A. A. Haruna, and I. A. Mohammed, "Selecting the best municipal solid waste management techniques in Nigeria using multi criteria decision making techniques," *Reports in Mechanical Engineering*, vol. 2, no. 1, pp. 180–189, 2021.

[42] D. T. Do, "Application of FUCA method for multi-criteria decision making in mechanical machining processes," *Operational Research in Engineering Sciences: Theory and Applications*, vol. 5, no. 3, pp. 131–152, 2022.

[43] M. Baydas, "Comparison of the performances of MCDM methods under uncertainty: An analysis on bist SME industry index," *OPUS Journal of Society Research*, vol. 19, no. 46, pp. 308–326, 2021.

[44] M. Baydas and O. E. Elma, "An objective criteria proposal for the comparison of MCDM and weighting methods in financial *performance* measurement: An application in BORSA ISTANBUL," *Decision Making: Applications in Management and Engineering*, vol. 4, no. 1, pp. 257–279, 2021.

[45] J. C. Pilligrin, P. Asokan, J. Jerald, and G. Kanagaraj, "Effects of electrode materials on performance measures of electrical Discharge micro-machining," *Materials and Manufacturing Processes*, 2018.

[46] R. Kitada, K. Fujii, R. Wang, and A. Okada, "Effect on mold releasability on EDM finished surface using powder mixed working fluid," *International Journal of Electrical Machining*, no. 23, pp. 24–31, 2018.

[47] N. H. Quang, L. X. Hung, N. T. Tu, T. Q. Hoang, and V. N. Pi, "A comparative study on multi-criteria decision-making in dressing process for internal grinding," *Machines*, vol. 10, 303, 2022.

[48] N. H. Quang, N. V. Tung, P. D. Phong, T. Q. Hoang, and V. N. Pi, "Multi-criteria decision making in the PMEDM process by using MARCOS, TOPSIS, and MAIRCA methods," *Applied Sciences*, vol. 12, 3720, 2022.

[49] N. H. Phan, B. T. Long, L. Q. Dung, N. D. Toan, and T. Muthuramalingam, "Multi-criteria decision making using preferential Selection index in titanium-based die-sinking Pmedm," *Journal of the Korean Society for Precision Engineering*, vol. 36, no. 9, pp. 793–802, 2019.

[50] S. Rajamanickam and J. Prasanna, "Multi objective optimization during small hole Electrical Discharge Machining (EDM) of Ti-6Al-4V using TOPSIS," *Materialstoday: Proceedings*, vol. 18, no, 7, pp. 3109–3115, 2019.

[51] B. Prasetiyo, N. Baroro, and D. E. Rufiyant, "Fuzzy simple additive weighting method in the decision making of human resource recruitment," *Lontar Komputer*, vol. 7, no. 3, pp. 174–181, 2016.

[52] C. H. Che Haron, J. A. Ghani, Y. Burhanuddin, Y. K. Seong, and C. Y. Swe, "Copper and *graphite* electrodes performance in electrical-discharge machining of XW42 tool steel," *Journal of Materials Processing Technology*, vol. 201, pp. 570–573, 2008.

[53] A. Muttamara, W. Borwornkiatkaew, A. Pronpijit, and S. Nuanchom, "Effect of graphite electrode to surface's characteristic of EDM," in *Proc. MATEC Web of Conferences*, 2016, vol. 7, 01002, pp. 1–4.